Chapter 12
Early Warning Against Insolvency of Enterprises Based on a Self-learning Artificial Neural Network of the SOM Type

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Abstract The article describes the use of a self-learning neural network of the SOM type to forecast insolvency of enterprises in construction industry. The research was carried out on the basis of information regarding 578 enterprises that went into bankruptcy in the years 2007–2013. These entities constituted a sample singled out from a population of 4750 enterprises that went bankrupt in Poland during that time, for which it was possible to obtain financial statements in the form of balance sheets and profit-and-loss accounts for the period of 5 years prior to the bankruptcy. Twelve (12) variables in the form of financial analysis indicators have been assessed, which are most commonly used in the systems of early warning about insolvency. The network constructed allowed effective classification of nearly all entities as insolvent a year before the announcement of their bankruptcy.

Keywords Bankruptcy · Insolvency · Artificial neural network · Forecasting

12.1 Introduction

Current analytical and controlling practice uses, among others, information from the financial statements of enterprises. The value of this information is as much useful as it allows diagnosing not only the events from the past, but also inferring about the future of an enterprise. Along with the increase in the multiplicity and the level

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of the complexity of the relationships occurring between business entities, the risk of cooperation with entities that become financially ineffective in business trading increases. In accordance with the bankruptcy law applicable, not only in Poland [1, 2], but in other legislations (e.g., EU [3]), insolvency of these entities may, in an extreme scenario, lead to their bankruptcy. This, in turn, means very serious problems [4] involving collection of the claims due on the part of the cooperators, who become unsatisfied creditors.[1]

Explicitly for the needs of economic practice, a stream of research on improvement of the systems of early warning about insolvency (bankruptcy) of enterprises has been developed within the theory of economic sciences, particularly in the discipline of finance and management [5]. Most often, these systems are mainly based on the integrated indicators of financial analysis in the form of a discriminant function [6]. A well-executed financial analysis supports the decision-making processes of managers in many aspects (areas) of an enterprise's operations.

Numerous empirical studies exhibit the need to analyze the changes occurring over time in a large number of various entities, the state of which is described by many parameters. Such needs also exist in the financial analysis of enterprises, particularly in that oriented not so much on traditional (*ex post*) assessment of the economic and financial condition of business entities, but rather on the so-called prospective (*ex ante*) assessment, i.e., an analysis preceding the assessment of their ability to function on the market. Conduction of a study on these entities, using a traditional index analysis referring to separate areas of entity functioning (such as assessment of financial liquidity, debt service capacity, profitability and productivity or the turnover) does not allow drawing objective general conclusions, but only a fragmentary evaluation of the examined entity.

In order to determine the scoring, particularly that focused on a future assessment of an enterprise's survivability on the market, the theory of economic sciences has developed various methods and techniques of business research. In the field of research on improvement of the systems of early warning about insolvency, advanced computational techniques are used, among others, including self-learning artificial neural networks.

The main objective of this study was to construct a neural network of the SOM (*self-organizing map*) type, enabling diagnosis and early capture of the quantitative symptoms of an insolvency threat (de facto a bankruptcy threat) in enterprises. In the process of creating an SOM neural network, 12 variables were used, constituting selected indicators of financial analysis, calculated for 578 enterprises in the construction industry, which went into bankruptcy in Poland during the years 2007–2013.

The main goal of the study formulated as such allowed assumption of the following research hypothesis: The use of an artificial neural network of the SOM type

[1] International-wise, a synthetic description of the functionality of bankruptcy registers of EU member states, which in the future is to become a centralized database system, is available on the European Justice Web site: https://beta.e-justice.europa.eu/110/PL/bankruptcy_and_insolvency_registers; (accessed on: September 11, 2018).

enables a diagnosis of an enterprise's financial condition and its observation in a time perspective.

As the authors' previous research experience and the literature studies in this area indicate that a classification analysis aimed at detecting the risk of enterprise bankruptcy (with a minimum 1-year forecasting horizon) is difficult, due to the existence of many factors, the first involves the selection of the variables, in the form of the financial indicators that should be taken under consideration. The indicators that seem to be most appropriate, from the perspective of their construction and interpretation, often insufficiently differentiate the entities under examination. Namely, due to their statistical properties, they are not suitable for distinction of the enterprises that are threatened with bankruptcy. Another problem is the construction of a synthetic index that would be able to jointly take into account the variables expressed on different measurement scales. Typical aggregate indicators are of no use here. It seems that the above problems can be solved by basing the analysis on self-learning artificial neural networks. Such a network allows to detect the variables significantly differentiating the set of objects, while the neuron's structure ensures construction of an aggregate of the objects being described by the variables of almost any measuring scale.

12.2 Research Methodology, Description of the Research Sample and Justification for the Selection of the Research Problem

Research on the assessment of the effectiveness of using a self-learning neural network of the SOM type for the purpose of early warning about bankruptcy of enterprises has been based on the results of ratio analyses of a population of enterprises that went bankrupt in Poland in the years 2007–2013. In total, statistical data for all 4750 companies that filed for bankruptcy were collected during the 7-year research period, i.e., starting from 2007: 446 business entities and successively 422, 694, 679, 726, 893 and 890 business units in 2013 [7].

The population structure of these bankruptcies includes enterprises with diversified profiles of their business operations. Nevertheless, the most significant (most numerous) group of the entities, homogenous in terms of the industry, were the bankruptcies of construction companies (20.69% without considering industrial processing), whose business activity, in particular, involved:

- construction works related to erection of buildings;
- construction works related to the construction of civil engineering structures;
- specialized construction works.

During the 7-year research period, the share of the bankruptcy of construction companies increased significantly, on average, by 33.14% each year. Generalizing the conclusions on the structure of bankruptcy during this period, it should be emphasized that in Poland, in recent years, almost every second bankruptcy concerned enterprises from the construction industry (taking into account not only the strictly service activity, but also the production for this sector). Therefore, it seems reasonable to attempt the development of a diagnostic tool that would enable assessment of the economic and financial condition, aimed at early warning about the bankruptcy of enterprises from the construction sector. A review of the literature in this area clearly indicates the dominance of models without their sector-specific distinction and dedication to the enterprises of specific sectors.

From the population of the enterprises that went bankrupt during the research period, we managed to obtain financial statements of 2739 business entities by analyzing court files (from the National Court Register) containing financial statements for at least 4 years preceding the court declaration of bankruptcy. At the same time, it should be emphasized that the process of obtaining these data is extremely difficult, since it covers the business entities whose functioning was affected by the escalation of the economic crisis and resulted in a court ruling on the debtor's insolvency, that is bankruptcy. The files of these entities are often incomplete and are kept in the prosecutor's office, by the judges who deal with the case or the syndicates (currently replaced by restructuring advisors). This largely hinders the development of early warning models, since the financial data precedent to the bankruptcy, quite difficult to obtain, constitutes the basis for estimation of such models. Ultimately, 578 construction companies constituted the sample analyzed in this study, for which 12 financial analysis indicators were calculated for the period of 4 years prior to the announcement of bankruptcy:

1. The Current Ratio—a quotient of the current assets and the short-term liabilities of an enterprise, calculated at the end of a given reporting period.
2. The Debt Ratio (of external financing)—a quotient of the sum of long- and short-term liabilities, in relation to the balance sheet total, calculated at the end of a given reporting period.
3. The Productivity Ratio of Assets—a quotient of the sales revenue generated, in relation to the average annual value of the balance sheet total.
4. The Return on Total Assets (ROA)—a quotient of the net financial result, in relation to the average annual value of the balance sheet total.
5. The Return on Investment Ratio (ROI)—a quotient of the operating result, in relation to the average annual value of the balance sheet total.
6. The Net Cash Flow to Total Liabilities Ratio—being the ratio of the value of the net financial result adjusted (*in plus*) by amortization, in relation to the average annual value of long- and short-term liabilities.
7. The Self-financing Ratio of Assets—the share of equity (own capital) in the total financing of business operations, calculated at the end of a given reporting period.
8. The Short-term Receivables Turnover Ratio (in days)—a quotient of the average annual value of short-term receivables and the contractual number of days in a year (365), in relation to the sales revenues achieved in a given reporting period.

9. The Inventory Turnover Ratio (in days)—a quotient of the average annual value of the inventories and the contractual number of days in a year (365), in relation to the sales revenues achieved in a given reporting period.
10. The Gross Margin Ratio—a quotient of the gross financial result, in relation to the value of the sales revenues achieved in a given reporting period.
11. The Quick Ratio—a ratio of the difference between the current assets and the inventories (tangible current assets), in relation to the value of short-term liabilities;
12. The Working Capital to Total Assets Ratio—a quotient of the difference between the current assets and the current liabilities, in relation to the balance sheet total, calculated at the end of a given reporting period.

Selection of the above-listed 12 variables for construction of the artificial neural network was carried out based on the analysis of the frequency of the occurrence of the financial analysis indicators in 29 discriminant functions developed (by Polish scientific and research units) using a sample of enterprises located in Poland, which was aimed at early detection of the quantitative symptoms of enterprise bankruptcy [8].

12.3 Neural Networks of the SOM Type in Forecasting Enterprise Bankruptcy—Methodological Aspects

One of the types of artificial neural networks that are widely used in socioeconomic research is the self-learning networks. The self-learning neural networks is a non-model process of mapping the objects' space of entrance into the low-dimensional space of a small number of functional units, neurons, maintaining the topographical similarity of the objects. The group of self-learning networks includes, among others, neural networks of: the SOM (*self-organizing map*) type [9], the GSOM (*growing self-organizing map*) type [10], the HSOM (*hierarchical SOM*) type [11], the NG (*neural gas*) type [12], the GNG (*growing neural gas*) type [13], the GSOM+GNG type [14]. Self-learning networks are used in various disciplines and fields of science [15]. They are used, for example, to analyze shopping habits and preferences [16–19], to forecast the threat of bankruptcy of enterprises [20–22] and to diagnose the financial condition of enterprises [23].

One of the self-learning networks used quite frequently is the SOM network, also referred to as the Kohonen network or map, proposed and developed around 1982 by a Finnish professor Teuvo Kohonen. It is now one of the most well-known unsupervised models of artificial neural networks. The SOM network is modeled on a biological phenomenon called a *retinotopy*. It is one of the best-known and effective data mining applications, mainly used for classification, grouping, dimensionality reduction, searching for anomalies and deviations from typical values, visualization of multidimensional data sets and studies on the dynamics of phenomena [24–28].

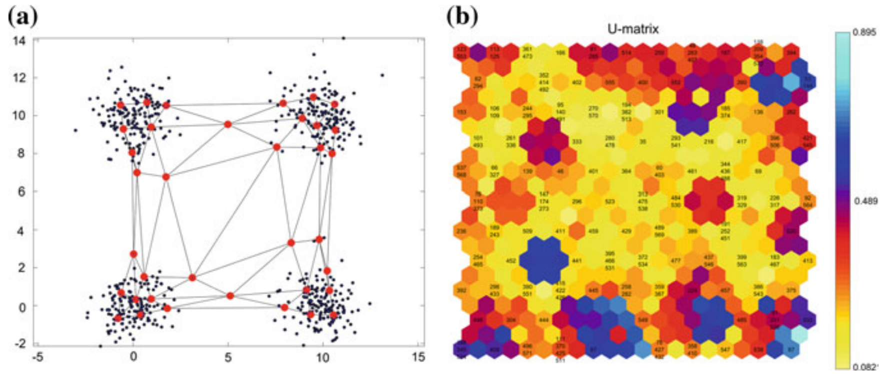

Fig. 12.1 **a** Neural network of the SOM type in the feature space; **b** Matrix of unified feature distances (*Source* Own elaboration)

The algorithm for building an SOM network is well established in the literature on the subject [14, 29]. In the first stage of building of the network, neurons are placed in the initial feature space, which then become the local approximators of the analyzed objects. The neurons are ordered in a certain structure called a network, where they are in certain relationships with each other. The network is "pre-scattered" in the space of objects (see Fig. 12.1a).

Following that, alternate objects are shown in the network. The neuron that is closest to the given object is the "winner" neuron, and it is subject to learning (change of weight, coordinates in space, approaching the object presented). That neuron's neighbors also learn, proportionally to the distance in which they are from the winner neuron. Some neurons never become a winner and act as "middlemen," allowing the network's fuller expansion in space. They are the so-called dead neurons. An SOM network can have the structure of a chain, a rectangle or a square. Each network structure adopted has different properties, while selection of an appropriate structure for a given research problem is crucial. The most commonly used network structure is the square network, which allows recognition of clusters in any geometric configuration, being a great tool for visualizing multidimensional data. At the same time, the square structure is the least economical and learns the longest. Table 12.1 shows the basic properties of an SOM network.

12.4 Neural Networks of the SOM Type in Forecasting Enterprise Bankruptcy—Results of Empirical Research

The empirical analysis took into account 578 enterprises described by 12 financial indicators, as of 4 years prior to their bankruptcy. After elimination of the enterprises for which there were numerous data gaps in the values of the indicators and the

Table 12.1 Properties of the SOM network

Properties	SOM network
Network structure	Constant
Number of critical control parameters	4
Grouping quality at optimal parameters	High
Learning speed	Average
Memory capacity requirements	Large
Any configuration of clusters	Yes
Dead neurons	Yes
Twisting of the network	Yes
Fuzzy of the clusters	Acceptable (small classification errors)
Non-separable clusters	Acceptable (small classification errors)
Visualization of multidimensional data	Yes
Network visualization	Yes
Data mining tool	Yes

Source Own elaboration

enterprises whose indicator values were below the 1st percentile of or above the 99th, 177 enterprises were used to build the network.[2] Considering the number of these objects, as well as the number and the statistical properties of the financial indicators, an SOM network was built with a hexagonal structure of neuronal connections, a Gaussian neighborhood function and a size of 11 × 11 neurons. The network is characterized by a small average quantization error (0.0662), topographical error (0.2542) and distortion error (0.0078). Its graphical representation, in the form of a map of unified distances, is shown in Fig. 12.1b. The color at the bottom of the scale signifies the minimum existing distances, at the top—the maximum ones.

Based on the analysis of the map of unified distances, four clusters of enterprises that are characterized by a similar financial situation, as part of the class, have been identified (see Fig. 12.2a, b). Clusters 1 and 2 include enterprises whose financial situation is definitely unfavorable. These are the companies that were at the highest

[2] In accordance with the adopted research methodology, described in the first part of the study, the construction enterprises that went bankrupt in the years 2007–2013 have been described by financial analysis indicators and subjected to the indicator analysis. The indicators that required averaging of the balance sheet values, which directly results from the calculation procedure used in the financial analysis, should contain data for the reporting periods even 5 years prior to the year in which the bankruptcy took place. This often caused numerous data gaps, because despite the obligatory submission of such documents to the commercial courts, the entities subjected to restructuring transformations, particularly those at risk of bankruptcy, did not meet this obligation. The lack of sanctioning of the law in this aspect poses a big problem for the development of research on the models of early warning about bankruptcy, because it prevents acquisition of financial data regarding these entities, see e.g., [30].

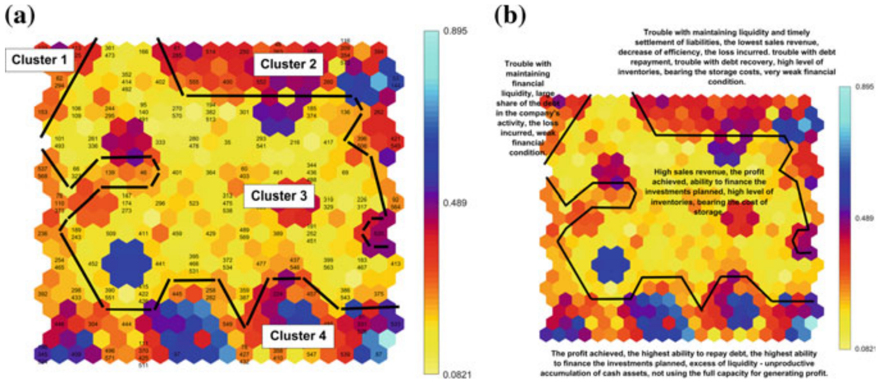

Fig. 12.2 **a** Division of enterprises into homogenous clusters; **b** Description of the clusters distinguished based on the financial analysis indicators (*Source* Own elaboration)

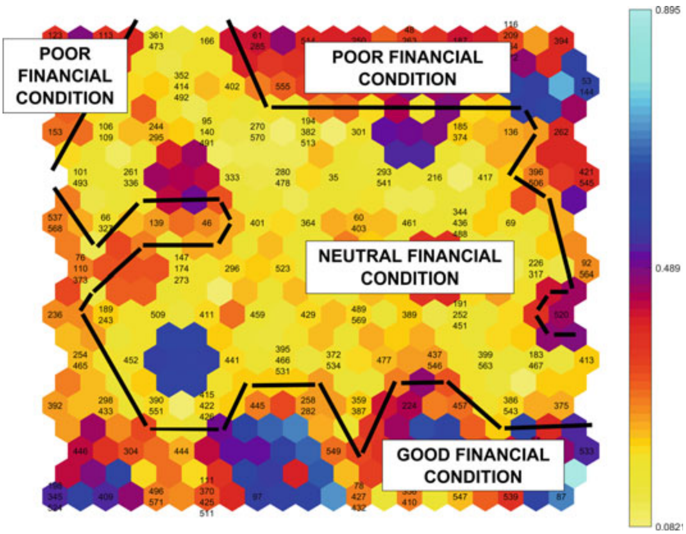

Fig. 12.3 Map of the enterprises' financial condition (*Source* Own elaboration)

risk of bankruptcy.[3] Appearance of an enterprise in this area of the SOM network should be considered as a serious warning sign. In cluster 3, there are enterprises that are characterized by a neutral financial condition. The values of the analyzed indicators for the entities in this group are at the level considered to be average, while in cluster 4, there are companies whose financial ratios suggest that they are in good financial condition (see Fig. 12.3).

[3]This risk was materialized in the form of a court ruling on the bankruptcy of these entities in the ($t0$) period.

The SOM shown in Fig. 12.3 presents, in a static manner, the enterprises' situation 4 years prior to the bankruptcy. In the further part of the study, the values of the indicators for the examined enterprises, from the following three reporting years, were plotted on the map. This allowed observation of the changes in the financial condition of the researched enterprises.

Figure 12.4 shows the changes in the position of four sample companies on the map of uniform distances. These points correspond to subsequent reporting periods in which financial results were announced, from (*t*-4), that is 4 years prior to the company's declaration of bankruptcy, to (*t*-1), that is the year of publication of the last financial report before its bankruptcy.

The charts (see Fig. 12.4) show that in the (*t*-4) period, the enterprises were in the area of those with good or neutral financial condition. They remained in this area for 1, 2 or 3 years, and in the (*t*-1) period, they always moved to the area of units with poor financial condition. Regardless of the starting point on the SOM, after 4 years all the enterprises moved to the clusters of the companies with the lowest values of the financial indicators. Very interesting conclusions were also made while analyzing the clustering path in the period of 4 years prior the bankruptcy announcement, on which the companies that went bankrupt in the year (t0) moved. It turned out that

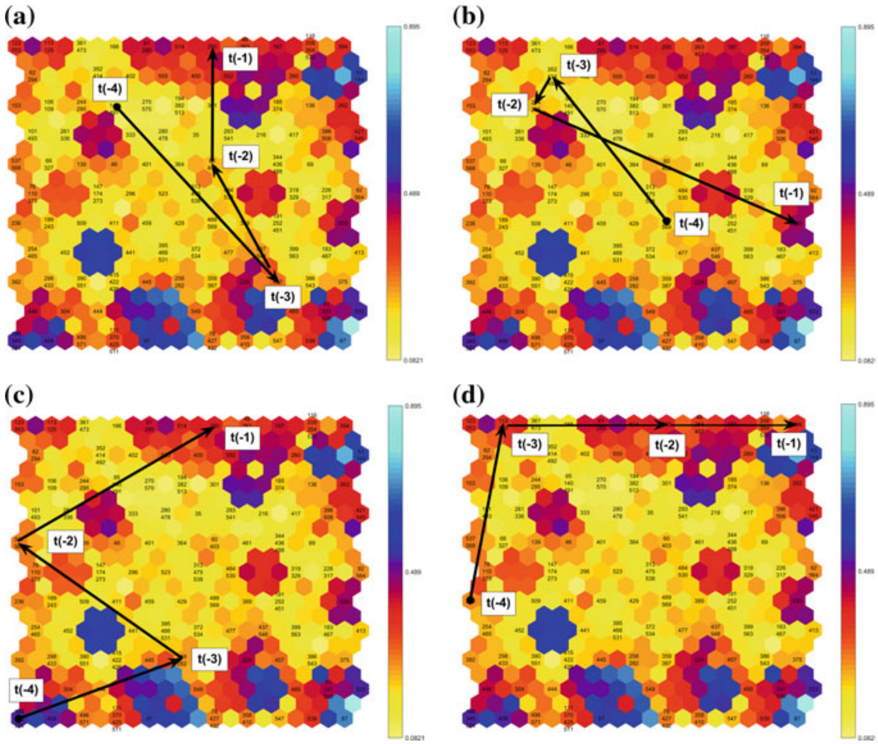

Fig. 12.4 Trajectories of four sample companies (*Source* Own elaboration)

52.5% (93 entities) of the analyzed bankruptcies in the periods (t-4) to (t-2) were in cluster 3 (thus having a neutral economic and financial condition). Their ability to stay on the market has dropped dramatically only 1 year before bankruptcy, which is why they moved to cluster 1 or 2.

In the set of the examined bankruptcies, there were also such entities (20 cases), which 4 years prior to the bankruptcy were in cluster 1 or 2, then, within subsequent 2 years, moved to cluster 3—i.e., the units with a neutral economic and financial condition, and a year before the final court declaration of bankruptcy—again they were classified within cluster 1 or 2. The results of these partial studies confirm the hypothesis put forward in the literature on the subject about a possible, earlier than the usually assumed 1 year, forecasting of solvency (market survival capability) of business entities.

Out of the 177 companies that were analyzed in the study, 176 were correctly classified in the area of the enterprises with poor financial standing. Only one exception was observed in the study—the enterprise which even in the (t-1) period did not move to cluster 4.

12.5 Conclusion

The study presented here certainly is not exhaustive. Only 177 enterprises were taken into consideration, which after the announcement of the financial results for the t(-1) period declared bankruptcy. The SOM network presented, however, allows the information that is extremely useful for the company's management to be easily read from the map. Identification of the "safe" and the "dangerous" areas allows to control the changes in the financial standing of the entities being observed. The company's moving from the "safe" area to the "dangerous" one is a serious warning sign, indicating that the company should be closely watched. At the same time, the enterprises located in the area of risk may come out of it, which can be interpreted as effective remedial actions taken by the companies' managements and improvement of their overall situation.

SOM networks surely are worth to be included in the set of the tools used by decision makers. It seems that networks of this type perfectly complement and often replace other analytical tools.

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